Risk of Internet Money Market Funds and Its Spillover Effect: Based on La-VaR, DCC-GARCH and Minimum Spanning Tree

Huizi Ma, Yuting Wang, Lin Lin, Xiangrong Wang*

College of Mathematics and Systems Science, Shandong University of Science and Technology, China
skd991250@sdust.edu.cn, wangyt108@163.com, linlin2020ll@163.com, sdust_wang@126.com

Abstract

Internet money market funds (IMMFs) are China's most wildly participated Internet financial products. This research mainly focused on the liquidity risk of IMMFs by establishing a La-VaR model with the cost of unit liquidity and further discussed the liquidity risk spillover between different IMMFs with La-VaR and minimum spanning tree algorithm. The results show the following: (a) The proposed La-VaR model is superior to the conventional VaR in evaluating the liquidity risk of IMMFs. The case study on Yu'E Bao also proves its superiority. (b) IMMFs with greater yield volatility face more significant liquidity risk pressure. (c) Risk spillover effects exist in IMMFs, and IMMFs with an extensive fund scale are more likely to spread liquidity risk to the entire market.

Keywords: Internet money market funds, Liquidity risk, La-VaR, Risk spillover effect

1 Introduction

Recent years have witnessed a spurt development of Internet finance in China. Internet money market funds (IMMFs), also known as Internet money funds, are Internet financial products with the broadest social participation. IMMFs usually gather idle funds of individual investors to obtain profit with the help of internet wealth management platforms [1-2] and have long been lucrative for shareholders and fund firms. Take the largest IMMF in China, Yu'E Bao, as an example; its scale was up to about 764.578 billion Yuan (approximately 120.19 billion dollars) as of the end of the third quarter of 2021.

IMMFs are characterized by low risk and high liquidity, as most IMMFs implement the "T+0" or "T+1" purchase and redemption business model and can be quickly purchased and redeemed. Therefore, appropriate monetary liquidity is essential for IMMFs. Meanwhile, the continuous redemptions could exert liquidity pressure on IMMFs represented by Yu'E Bao.

IMMFs derive from money market funds (MMFs). How the liquidity risk manifests itself in the MMFs has long been neglected in academic theory until the stressed condition of subprime markets, and in 2013, Bengtsson [3] proved that the liquidity risk of European MMFs not only trigger the market crisis but also can transfer to a wider financial system. Gao et al. [4] argued that the optimal cash reserve ratio played an essential role in controlling the liquidity risk of Yu'E Bao in 2018. Later, Yang et al. [5] suggested that liquidity risk was regarded as the main factor in Yu'E Bao's investment strategy, and liquidity risk was exceptionally high when investors had strong consumption demand in 2019. Zhang et al. [6] suggested that an optimal liquidity ratio can also be used to evaluate liquidity needs in 2020. Liquidity-adjusted risk models based on the idea of bid-ask spread were brought by researchers [7-9], but the liquidity risk evaluation of IMMFs still needs to be further explored.

Internet finance's network structure and cluster characteristics also lead to the spread and spillover of risks from the Internet finance market to other financial needs. In 2020, Xu et al. [10] discussed the relationship between contagion and contagion among different risk factors in Internet finance. They concluded that risks were transmitted externally through the internal circulation of Internet finance. Dong et al. [11] found that the development of Internet finance had a negative impact on the liquidity of commercial banks in 2020. Then, Zhao et al. [12] discussed the credit risk contagion of peer-to-peer lending based on complex theory and SEIR model and found that platform correlations, contagion latency, and other factors influenced the risk transition in Internet finance in 2021. Fan et al. [13] verified that excessive network connectedness among financial institutions would amplify financial shocks through contagion effects in 2021. Their results show that the systemic risk contagion in different sectors shows heterogeneity.

According to the literature analysis, current research mainly studies the liquidity risk and risk contagion of traditional MMFs and Internet finance. However, how to effectively measure the liquidity risk of IMMFs? Are there any risk spillover effects between different IMMFs? How to determine the risk contagion path of the IMMF network? The questions above still need to be thoroughly investigated. Therefore, we introduced the cost of unit liquidity to establish a liquidity adjusted value-at-risk (La-VaR) framework to access the IMMFs' liquidity risk and applied DCC-GARCH to access the risk spillover effect of IMMFs. Besides, the minimum spanning tree (MST) algorithm was used to construct IMMFs' risk contagion path network. The analysis has practical significance to provide valuable references and suggestions for the risk prevention and control of the Internet financial product market.

2 La-VaR and CoVaR Model

2.1 VaR Calculations

*Corresponding Author: Xiangrong Wang; E-mail: sdust_wang@126.com
DOI: 10.53106/160792642022072304003

VaR is the maximum possible loss of a financial institution or portfolio for a specific period of time at a given confidence level. It is defined as follows:

$$\text{Prob}(\Delta P < \text{VaR}) = 1\text{-}\alpha \tag{1}$$

Where ΔP is the loss during the holding period, $1\text{-}\alpha$ is the confidence level (α =0.05).

We used the GARCH model to calculate the VaR. Also, to emphasize the correlation of different yield volatility sequences, we constructed a binary DCC-GARCH model between IMMFs.

Suppose the yield rate of IMMF *i* and IMMF *j* at a given time *t* is

$$x_t = \mu_t + e_t \tag{2}$$

Where $X_t = \left(x_t^i, x_t^j\right)$, $\mu_t = \left(\mu_i, \mu_j\right)$, $e_t = H_t^2 \varepsilon_t$.

The covariance matrix H_t can be expressed as

$$H_t = D_t R_t D_t \tag{3}$$

Where $D_t = \begin{bmatrix} \sqrt{h_t^i} & 0 \\ 0 & \sqrt{h_t^j} \end{bmatrix}$, $R_t = \begin{bmatrix} 1 & \rho^{i,j} \\ \rho^{j,i} & 1 \end{bmatrix}$. R_t represents the dynamic conditional correlation matrix, while $\rho^{i,j}$ is the correlation coefficient between IMMF *i* and IMMF *j*.

The estimations of the volatility h_t^i and h_t^j are calculated with equation (4)

$$h_t = \alpha_0 + \sum_{p=1}^{m} \alpha_p \varepsilon_{t-1}^2 + \sum_{q=1}^{n} \alpha_q h_{t-1}^2 \tag{4}$$

Correlation matrix Q_t is introduced to represent R_t in the DCC model. Then

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{5}$$

Where $Q_t = \begin{bmatrix} q_t^{i,i} & q_t^{i,j} \\ q_t^{j,i} & q_t^{j,j} \end{bmatrix}$. Meanwhile, $q_t^{i,j}$ is the covariance of X_t^i (IMMF i's yield rate) and X_t^j (IMMF *j*'s yield rate). Q_t is a positive definite matrix.

Define Q_t as

$$Q_t = \left(1-\alpha-\beta\right)\overline{Q} + \alpha(\varepsilon_{t-1}^i \varepsilon_{t-1}^j) + \beta Q_{t-1} \tag{6}$$

Where $\alpha + \beta < 1$. $\overline{Q}$ is the unconditional variance matrix of residual error ε_t.

The maximum possible loss of IMMF *i* at a given confidence level is $VaR_{q,t}^i$, which can be expressed as

$$VaR_{q,t}^i = \hat{\mu}_t^i - Q(q)\hat{h}_t^i \tag{7}$$

Where

$\hat{\mu}_t^i$ is the value estimated by the GARCH model.

$\hat{h}_t^i$ is the standard deviation calculated by the DCC-GARCH model.

$Q(q)$ is the corresponding quantile at confidence level 1-q.

2.2 La-VaR Framework

The conventional VaR model assumes that investors can sell all positions at a fixed price in the market in a specific period of time. However, the asset price is constantly fluctuating, and the assumptions of the conventional VaR model ignore the liquidity risk of financial assets. Considering that the ability to trade financial assets quickly cannot fully reflect the multi-dimensional and depth of IMMFs' liquidity, the parameter can still reflect the financial market's liquidity situation to a certain extent, hence here we discuss the liquidity-adjusted-risk model based on the relative spread of IMMFs.

At a specific moment, investors will sell certain positions of financial assets according to actual market conditions. In view of the relative spread volatility, investors need to consider factors such as the fluctuation of the mid-price and the spread so that the investment assets' actual risk can be calculated more accurately. Bangia et al. [7] measured liquidity risk based on relative bid-ask spreads based on the above ideas. They used the relative maximum price difference between the highest and the lowest bid price to measure stock liquidity. Bleaney and Li [14], Le and Gregoriou [15] suggested that the high-low spread can provide a relatively low standard deviation and is convenient to calculate.

According to IMMF redemption rules, if the redemption amount reaches the IMMF's upper limit on the day, it will lead to delayed redemption. After that, the investors will bear the risk of yield rate changes. The difference in income caused by delayed redemption will be defined as the liquidity cost used to measure the liquidity risk of the IMMFs.

This research constructed the relative bid-ask spread sequence of IMMFs, and further established the IMMFs La-VaR framework based on the research proposed by Bangia et al. [7] to assess the market risk that IMMFs face.

Relative bid-ask spread *S* is defined as

$$S = \frac{(Ask_i - Bid_i)}{(Ask_i + Bid_i)/2} \tag{8}$$

The average value of relative bid-ask spread $\overline{S}$ is

$$\overline{S} = \frac{1}{k}\sum_{i=1}^{k} \frac{(Ask_i - Bid_i)}{(Ask_i + Bid_i)/2} \tag{9}$$

The assets of IMMFs mainly include cash, bonds, stocks, etc. The liquid asset that can directly respond to investors' redemption requests is cash. Therefore, cash holdings can represent the maximum daily redemptions of each IMMF to some extent. We refer to references [7-9], and include the idea of relative bid-ask spread in the liquidity risk assessment for IMMFs. Though the proportion of cash can only partially reflect liquidity and has certain defects, this indicator can still reflect the potential liquidity risk of IMMFs to a certain extent, and the data can be obtained. Then, based primarily on the relative bid-ask spread S (see equation 8), we define the relative spread of IMMFs yield as

$$S_t = \frac{|r_{t+1} - r_t| \cdot (1\text{-}a) \cdot v}{(r_{t+1} + r_t)/2} \quad \textbf{(10)}$$

Where
S_t is the relative spread of IMMF at time t.
r_t is the yield rate of IMMF at time t.
r_{t+1} is the yield rate of IMMF at time t+1.
a is the proportion of cash to total assets.
v is the fund size.

Since IMMFs vary significantly in size, the relative spread is unitized to make the calculation results comparable. That is, if the fund scale of an IMMF is 1, the expression of the unit relative price spread is:

$$S_t^* = \frac{S_t}{v} = \frac{|r_{t+1} - r_t| \cdot (1\text{-}a)}{(r_{t+1} + r_t)/2} \quad \textbf{(11)}$$

Further, the cost of unit liquidity (CUL, hereafter) of IMMF i is defined as:

$$CUL_i = [r_t(\overline{S_t^*} + Z_\alpha \sigma_{S^*})] \quad \textbf{(12)}$$

Where r_t indicates the yield rate of IMMFs at time t. $\overline{S_t^*}$, σ_{S^*} and Z_α represent the mean value, volatility, and quantile level of the IMMFs' relative spread, respectively.

Then, the La-VaR of IMMFs can be derived as

$$\begin{aligned} La\_VaR_i &= VaR_i + CUL_i = \\ \hat{\mu}_t^i &- Q(q)\hat{h}_t^i + [r_t(\overline{S_t^*} + Z_\alpha \sigma_{S^*})] \end{aligned} \quad \textbf{(13)}$$

2.3 CoVaR Model

Considering that the CoVaR model can analyze the risk correlation between financial institutions, we calculate the La-VaR series of different IMMFs based on equation (13) and then introduce the series into the CoVaR model to analyze the liquidity risk spillover effect of varying series of IMMFs.

According to the definition of risk spillover proposed by Adrian et al. [16], the risk spillover effect from IMMF i to j is defined as $\Delta CoVaR_q^{i,j}$, which can be calculated by the following equation

$$\Delta CoVaR_q^{i,j} = CoVaR_q^{i,j} - VaR_q^i \quad \textbf{(14)}$$

The risk spillover value of IMMF i is the difference between $CoVaR_q^{i,j}$ and its VaR_q^i value.

Furthermore, we can calculate the relative range of risk spillover. The calculation process of risk spillover ratio $\%CoVaR_q^{i,j}$ from IMMF j to IMMF i is as follows:

$$\%CoVaR_q^{i,j} = \Delta CoVaR_q^{i,j} / VaR_q^i \quad \textbf{(15)}$$

According to the La-VaR model established by introducing CUL, the liquidity risk spillover model can be further constructed. The value of $\Delta La\_CoVaR_q^{i,j}$ can be defined as

$$\Delta La\_CoVaR_q^{i,j} = La\_CoVaR_q^{i,j} - La\_VaR_q^i \quad \textbf{(16)}$$

Then, the calculation process of the risk spillover ratio $\%\mathrm{La}\_CoVaR_q^{i,j}$ of IMMF j to IMMF i is as follows:

$$\%\mathrm{La}\_CoVaR_q^{i,j} = \Delta La\_CoVaR_q^{i,j} / \mathrm{La}\_VaR_q^i \quad \textbf{(17)}$$

Our research defines the positive and negative liquidity risk spillover effect as follows: (a) If the conditional value at risk $La\_CoVaR_q^{i,j}$ of IMMF j to IMMF i is greater than the $La\_VaR_q^i$ of IMMF i, the risk spillover value $\Delta La\_CoVaR_q^{i,j}$ is positive. That is, the liquidity risk of IMMF j will have a positive spillover effect on IMMF i. Compared with the situation without external influence, this effect will increase the liquidity risk of IMMF i. (b) If the $La\_CoVaR_q^{i,j}$ of IMMF j to IMMF i is less than $La\_VaR_q^i$ of IMMF i, the value of $\Delta La\_CoVaR_q^{i,j}$ is negative. That is, the liquidity risk of IMMF j will have a negative spillover effect on IMMF i. Compared with the situation without external influence, this effect will reduce the liquidity risk of IMMF i.

3 Liquidity Risk Measurement of IMMFs

3.1 Sample and Descriptive Statistics

We divide IMMFs into three categories: IMMFs docked by online third-party payment institutions (TPPI); IMMFs docked by banks (BANK); IMMFs docked by fund companies (FUND). According to the classification of IMMFs, we selected 20 IMMFs as total research samples (see Appendix A). The 7-day annualized yield of the 20 IMMFs was used in our empirical study.

Data was extracted from Wind Database. Considering that IMMF "PenghuaTianli Bao" (Fund Code: 001666) docked by Suning Financial was released on July 22, 2015. To ensure the yield series' continuity and consistency, the sample period of this research are from July 22, 2015, to December 5, 2018. After eliminating invalid data, each yield series contains 825 daily data, with 15,675 daily observations.

To compare the yield fluctuations and establish the GARCH model for normality test, data was processed by first-order logarithmic difference. Accordingly, the yield sequence after first-order logarithmic difference (R_t) was obtained by the following equation:

$$R_t = \ln P_t - \ln P_{t-1} \quad \textbf{(18)}$$

Where P_t and P_{t-1} are 7-day annualized yields at time t and time t-1, respectively.

Table 1 summarizes descriptive statistics. The results in Table 1 show that the yield fluctuations of IMMFs docked by online TPPI are relatively stable.

Table 1. Descriptive statistics of the yield series P_t

IMMFs	Fund Code	Mean Value	Median	Maximum	Minimum	Std. Deviation
TPPI	000198	3.27	3.26	4.39	2.30	0.66
	001666	3.76	3.74	5.37	2.11	0.70
	000379	3.34	3.31	4.45	2.30	0.65
	000569	3.47	3.66	6.00	2.03	0.71
	000397	3.61	3.63	5.14	2.44	0.67
	000719	3.57	3.78	5.34	2.10	0.75
	000009	3.43	3.58	5.39	2.31	0.69
	000638	3.61	3.60	5.06	2.16	0.73
BANK	000359	3.67	3.75	4.74	2.52	0.65
	000600	3.72	3.72	4.90	2.73	0.56
	000730	3.46	3.42	6.46	2.14	0.79
	000693	3.41	3.29	4.57	2.36	0.64
	000528	3.26	3.14	4.83	1.98	0.75
	090022	3.29	3.26	6.23	1.62	0.86
	000588	3.52	3.64	4.62	2.36	0.68
FUND	000539	3.45	3.42	4.63	2.42	0.64
	200003	3.22	3.15	5.13	1.86	0.65
	000709	3.45	3.53	4.73	2.15	0.72
	150005	2.96	3.02	5.34	0.75	0.87
	320002	3.01	2.77	6.17	1.48	0.77

3.2 Stationarity, Autocorrelation, and ARCH Effect Test

The skewness, kurtosis, and Jarque-Bera statistics show that the series of yield changes of different IMMFs have prominent peaks, fat tails, and disobedient normal distribution (see Table 2). Therefore, we assume that the IMMFs yield series obey the GED distribution.

It is necessary to test the stability of the sample data to avoid pseudo-regression. We chose the ADF unit root test and P-P unit root test to test it. The results of Table 2 show that the sample sequence is stable at the 1% statistical significance level.

A 12th-order autocorrelation test was performed on the yield fluctuation series R_t. The results show that all sample sequences have autocorrelation. Before the ARCH effect test, the autocorrelation of each sample sequence should be eliminated. The yield fluctuation series of all the samples are calculated, and the ARCH-LM test is performed. Results are shown in Table 3.

The ADF test results, P-P test, and ARCH-LM test in Table 3 indicate that this research's data is suitable for the GARCH model.

3.3 Calculation of VaR

VaR can evaluate the market risk caused by the fluctuation of the IMMFs' yield. The results of sample IMMFs' VaR values are shown in Table 4.

According to Table 4, the IMMFs docked by the BANK have the smallest VaR value, followed by IMMFs docked by TPPI, while IMMFs docked by FUND have the most considerable VaR value.

The mean VaR values of both IMMFs docked by TPPI and those docked by BANK are relatively small. However, BoshiXianjin Bao A (000730) and NanfangXianjintong E (000719)'s VaR values are 0.0907 and 0.1040, respectively, which are relatively high among sample IMMFs. Yu'E Bao (000198) has the smallest VaR value (0.0091), followed by JianxinXianjintianli A (000693) with a VaR value of 0.0223.

From 2015 to 2018, BoshiXianjin Bao A (000730) and NanfangXianjintong E (000719) were similar in bond positions, and both tended to hold discounted treasury bonds. Therefore, the high VaR value of BoshiXianjin Bao A (000730) and NanfangXianjintong E (000719) might be caused by the bond yield fluctuation. Vulnerable to the significant fluctuation of these bond yields.

The VaR values of IMMFs demonstrated a downward trend. The trend denotes that with the constant maturity of the IMMF market and the increasingly deepening of market supervision, the IMMF market's stability is significantly improved.

According to the results of Table 1, the yields of Tianhong Yu'E Bao (000198), Jianxin Xianjintianli A (000693), and Zhongyin Huoqi Bao (000539) are around 0.65. Compared with other IMMFs in the same series, these three IMMFs' yield fluctuates slightly and have smaller VaR values. While the yields of NanfangXianjintong E (000719), BoshiXianjin Bao A (000730), and Yinhe Yinfuhuobi A (150005) fluctuate significantly according to Table 1, and the VaR value of these three IMMFs are relatively high as well. Therefore, the volatility of IMMF yields seems to be positively related to the market risk.

Table 2. Results of skewness, kurtosis, Jarque-Bera, ADF, and P-P unit root test

Fund Code	Skewness	Kurtosis	Jarque-Bera	P-Value	ADF Test	P-P Test
000198	0.30	20.03	9954.11	0.0000	-6.869368***	-23.63059***
001666	0.12	39.03	44527.36	0.0000	-14.85505***	-35.21103***
000379	-0.16	15.19	5096.72	0.0000	-13.92334***	-28.40223***
000569	-0.42	14.61	4650.49	0.0000	-14.62763***	-49.61836***
000397	-0.97	14.14	4385.01	0.0000	-13.75860***	-34.20439***
000719	-0.32	31.25	27390.16	0.0000	-8.966872***	-61.53152***
000009	-2.25	107.40	374471.30	0.0000	-10.38623***	-32.14487***
000638	0.04	23.68	14668.64	0.0000	-15.17073***	-42.19558***
000359	-1.56	36.62	39092.01	0.0000	-17.09316***	-33.14540***
000600	0.36	18.57	8333.55	0.0000	-14.83587***	-39.42767***
000730	-0.62	35.61	36529.22	0.0000	-12.49974***	-68.87799***
000693	-0.22	9.56	1481.84	0.0000	-12.39973***	-22.48298***
000528	0.33	35.46	36146.95	0.0000	-13.36771***	-25.74930***
090022	-0.11	11.54	2502.21	0.0000	-15.71859***	-72.91834***
000588	0.41	29.02	23243.20	0.0000	-18.48387***	-26.33631***
000539	-1.17	25.59	17684.54	0.0000	-12.87649***	-30.93436***
200003	-0.28	32.67	30206.70	0.0000	-13.34518***	-36.95674***
000709	-0.31	22.62	13216.96	0.0000	-13.58934***	-36.94890***
150005	0.66	21.31	11559.14	0.0000	-14.78879***	-51.95669***
320002	0.15	12.32	2980.76	0.0000	-13.31874***	-32.66581***

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Results of ARCH-LM test

Fund Code	Model	ARCH-LM Test	Fund Code	Model	ARCH-LM Model
000198	ARMA(2,1)	13.90759***	000730	ARMA(3,2)	36.55745***
001666	ARMA(1,1)	82.66874***	000693	ARMA(2,1)	7.963968***
000379	ARMA(2,2)	36.51586***	000528	ARMA(2,1)	14.49644***
000569	ARMA(1,2)	7.505313***	090022	ARMA(2,2)	32.74331***
000397	AR(2)	8.780539***	000588	ARMA(2,1)	27.4476***
000719	ARMA(1,3)	8.350532***	000539	ARMA(2,3)	14.50937***
000009	ARMA(2,2)	34.85728***	200003	ARMA(2,2)	33.97813***
000638	ARMA(1,3)	31.16863***	000709	ARMA(2,2)	13.95454***
000359	ARMA(2,2)	14.7154***	150005	ARMA(2,4)	26.74261***
000600	AR(1)	21.78246***	320002	ARMA(2,2)	27.03822***

*, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. VaR value of IMMFs

IMMFs		VaR				
		2015	2016	2017	2018	Mean
TPPI	000198	0.0149	0.0078	0.0053	0.0084	0.0091
	001666	0.0586	0.0747	0.0140	0.0173	0.0411
	000379	0.0718	0.0332	0.0165	0.0165	0.0345
	000569	0.0732	0.0662	0.0560	0.0340	0.0574
	000397	0.0835	0.0640	0.0339	0.0359	0.0543
	000719	0.2542	0.1048	0.0326	0.0244	0.1040
BANK	000009	0.1243	0.0394	0.0258	0.0155	0.0512
	000638	0.0649	0.0768	0.0461	0.0467	0.0586
	000359	0.0753	0.0648	0.0303	0.0148	0.0463
	000600	0.0765	0.0513	0.0249	0.0249	0.0444
	000730	0.2058	0.1167	0.0172	0.0230	0.0907
	000693	0.0363	0.0286	0.0119	0.0123	0.0223
	000528	0.1027	0.0397	0.0368	0.0351	0.0536
FUND	090022	0.0670	0.0550	0.0415	0.0279	0.0478
	000588	0.0698	0.0379	0.0134	0.0101	0.0328
	000539	0.0777	0.0452	0.0251	0.0154	0.0408
	200003	0.1026	0.0862	0.0574	0.0394	0.0714
	000709	0.1094	0.0743	0.0385	0.0232	0.0613
	150005	0.2417	0.1623	0.0915	0.0815	0.1443
	320002	0.1262	0.1270	0.1320	0.0765	0.1154

3.4 Calculation of La-VaR

This research defines CUL as a risk factor reflecting the liquidity risk of IMMFs and builds a liquidity-adjusted VaR framework incorporating liquidity risk. The La-VaR results are calculated according to equations 10-13 and are shown in Table 5.

The average La-VaR values in Table 5 report that the market risk of the IMMFs docked by TPPI is relatively small, while the IMMFs docked by FUND are relatively large. The difference is similar to the VaR calculation. The La-VaR value of BoshiXianjin Bao A (000730) and NanfangXianjintong E (000719) are 0.0966 and 0.1328, respectively, while Zhaoshang Zhaoqian Bao A (000588) and Tianhong Yu'E Bao (000198) are 0.0242 and 0.0117. The La-VaR value of the liquidity risk for IMMFs docked by FUND is high. This result may be the proportion of individual holding for TPPI and BANK IMMFs, and it is not easy to have large-scale centralized redemption. While FUND IMMFs generally have a higher institution holding proportion, it is easier to face centralized redemption, resulting in liquidity risk.

The yield results shown in Table 1 and the La-VaR value shown in Table 5 show a relationship that IMMFs with greater yield volatility face more significant liquidity risk pressure.

According to the time trend of La-VaR, the market risk of IMMFs is declining year by year, which shows a stable development momentum of the IMMF market.

3.5 Comparison of VaR and La-VaR

The traditional VaR does not highlight liquidity risk, and its estimation might cause an underestimation of losses [17]. We attempt to highlight the liquidity element by employing the CUL. The liquidity adjustment made by the La-VaR shows its superiority over the traditional VaR.

Still, it cannot reflect the increase of the liquidity risk component. Therefore, we further compared the VaR and La-VaR values and calculated the proportion of liquidity to explore the proportion of IMMFs liquidity risk (see Table 5).

The results in Table 5 show that the introduction of CUL increases the risk value of IMMFs. Then, we analyze the difference in the proportion of liquidity components in IMMFs.

First, most IMMFs' CUL accounts for more than 15% of their risk, with more than half of the samples of IMMFs accounting for more than 20%, and some account for about 30%. The empirical results are similar to the research of Bangia et al. [7]. They found that the risk measurement results of ignoring liquidity risk may underestimate the market risk of emerging markets by 25%-30%. Therefore, this research's empirical results prove that liquidity risk is one of the essential dangers faced by IMMFs.

Table 5. La-VaRvalue of IMMFs

IMMFs		La-VaR					Liquidity Proportion
		2015	2016	2017	2018	Mean	
TPPI	000198	0.0188	0.0097	0.0106	0.0076	0.0117	22%
	001666	0.0966	0.0883	0.0198	0.0223	0.0568	28%
	000379	0.0862	0.0417	0.0223	0.0210	0.0428	19%
	000569	0.0825	0.0752	0.0699	0.0497	0.0693	17%
	000397	0.1218	0.0893	0.0520	0.0510	0.0786	31%
	000719	0.3231	0.1318	0.0453	0.0311	0.1328	22%
	000009	0.1567	0.0494	0.0321	0.0189	0.0643	20%
BANK	000638	0.1034	0.0899	0.0617	0.0620	0.0792	26%
	000359	0.0863	0.0577	0.0363	0.0358	0.0540	14%
	000600	0.0890	0.0805	0.0391	0.0190	0.0569	22%
	000730	0.1538	0.1115	0.0866	0.0346	0.0966	6%
	000693	0.0324	0.0255	0.0241	0.0146	0.0242	8%
	000528	0.1131	0.0944	0.0556	0.0250	0.0720	26%
	090022	0.0878	0.0507	0.0439	0.0470	0.0574	17%
	000588	0.0555	0.0502	0.0336	0.0228	0.0405	19%
FUND	000539	0.0893	0.0699	0.0395	0.0134	0.0530	23%
	200003	0.1533	0.0976	0.0635	0.0477	0.0905	21%
	000709	0.1641	0.1211	0.0748	0.0377	0.0994	38%
	150005	0.2199	0.1993	0.1471	0.1123	0.1696	15%
	320002	0.1882	0.1572	0.1181	0.1096	0.1433	19%

Second, compared with IMMFs that are docked by BANK, those IMMFs docked by TPPI and FUND face more serious liquidity risk. The results of Table 5 show that the liquidity component of the IMMFs from the third-party payment institutions and the fund companies accounts for a relatively high proportion, which is basically above 20%. In contrast, the liquidity component of the IMMFs docked by BANK is relatively low.

The possible reasons are as follows:

Firstly, IMMFs docked by TPPI have financial management functions and have the consumption attributes. Yu'E Bao has launched a new business model of "T+0 subscription redemption", using the investor's account balance to purchase money funds automatically so that investors can not only enjoy income from an IMMF investment, capital in IMMFs can also be directly used for consumption, which attracts a large number of individual investors. The accumulation of idle funds makes IMMFs have more capital to operate, but it also puts higher requirements on IMMFs' liquidity risk management.

Secondly, the high liquidity risk of IMMFs is mainly caused by their asset allocation. IMMFs docked by FUND can only serve as wealth management products. Their high income can attract investors to invest. Therefore, IMMFs docked by FUND invest more in bonds, stocks, and other assets with more extended investment periods. The bank deposits they held to meet investors' redemption needs are relatively small, making the liquidity risk that IMMFs docked by FUND face relatively high. Among the sample IMMFs docked by FUND, the proportion of cash to net assets is less than 50% during the sample period. In particular, the cash holdings of YinheYinfuhuobi A (150005) and Nuoan Hubi A (320002) are only about 20%.

Thirdly, IMMFs docked by BANK are exposed to relatively less liquidity risk. On the one hand, most IMMFs docked by BANK adopt the "T+1" redemption mode. The investors propose a redemption request, and money will arrive the next weekday. This redemption mode gives the banks enough time to deal with investor redemptions. On the other hand, commercial banks can rely on their intense deposit preparations to meet great redemption demands and reduce liquidity risk.

4 Case Study

According to the above analysis, IMMFs from third-party payment institutions have a more significant average proportion of the liquidity risk. This section took Yu'E Bao (000198) as a case study to further analyze the liquidity-adjusted market risk trend of IMMFs.

Yu'E Bao is docked by Alipay, a third-party payment platform considered as China's PayPal, and funds in Yu'E Bao can be used directly for consumption. On holidays and festivals, the consumption of investors will increase remarkably. Then Yu'E Bao will face many redemptions and be prone to liquidity risk.

Czelleng [18] stressed that a clear understanding of market liquidity sources was essential to maintain financial stability and fine-tune policy makers' current regulations. Therefore, we plotted the liquidity-adjusted risk trend (see Figure 1). According to Figure 1, the liquidity-adjusted market risk faced by Yu'E Bao was markedly increased during the Double 11 Shopping Carnival, Christmas Day, traditional Chinese festivals, and summer holidays. However, although the risk of Yu'E Bao was raised during the 2017 Chinese Spring Festival, it was not as significant as in previous years. Besides, the liquidity adjusted risk during the first half of 2017 was low.

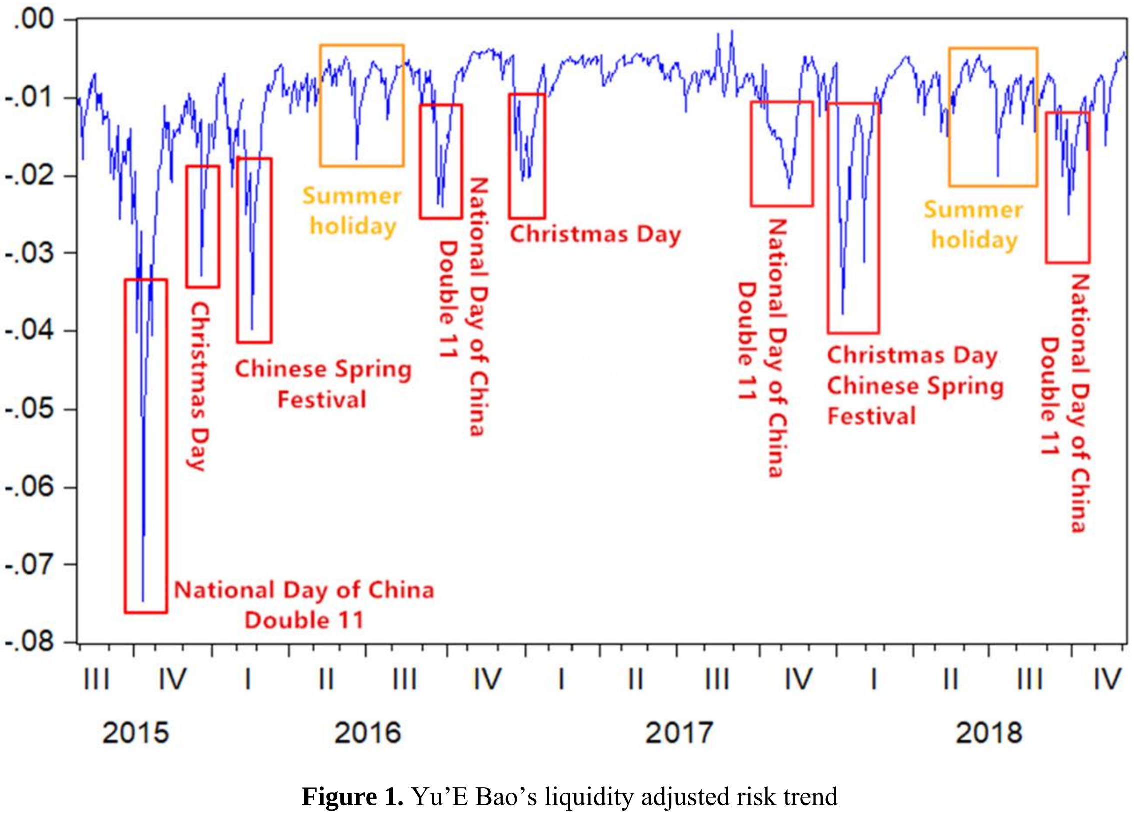


Figure 1. Yu'E Bao's liquidity adjusted risk trend

To regulate and control its overgrowth, Yu'E Bao began to limit investors' investment quotas in 2017. The holding limit of the personal trading account in Yu'E Bao changed from 1 million yuan to 250,000 yuan and then lowered again to 100,000 yuan. This regulation policy would reduce Yu'E Bao's difficulty in managing the liquidity risk to a certain extent. Simultaneously, the bank deposit holding rates of Yu'E Bao in the first three quarters of 2017 are 64.32%, 82.95%, and 87.11%, respectively, which helped Yu'E Bao control the pressure of fund redemptions and reduce the liquidity risk it face.

According to the temporal trend, Yu'E Bao showed significant liquidity risk since the fourth quarter of 2017, but not as dramatically as before. In December 2017, the Yu'E Bao personal trading account's daily subscription amount was adjusted to 20,000 yuan. Then the daily investment quota of

Yu'E Bao was limited since February 1, 2018. From June 6, 2018, "T+0 redemption" per day of Yu'E Bao cannot exceed 10,000 yuan. The limitation of daily redemption behaviors helped to control the liquidity risk.

Large-scale IMMFs such as Yu'E Bao significantly affect other money market funds, even the entire financial system. Once liquidity risk occurs, it will quickly spread to the whole financial market, making it easy to cause systemic liquidity risk. Therefore, our La-VaR framework can help solve the underestimation problems of IMMFs and reflect the liquidity risk situation of IMMFs.

5 Liquidity Risk Spillover Effect of IMMFs

5.1 DCC-GARCH Model

This section used the IMMF return series p_t calculated by the weight of IMMFs' size. Then first-order logarithmic difference was used to pre-process the yield series and generate the return fluctuation series r_t.

$$r_t = \ln p_t - \ln p_{t-1} \qquad \textbf{(19)}$$

Among them, p_t and p_{t-1} are the returns calculated by the weight of IMMF size at the time t and $t-1$.

To improve the fitting degree of the IMMFs return series, we introduced the binary DCC-GARCH model. We fit the single GARCH model with the change series of return rate r_t and then fit the DCC-GARCH model according to the obtained standardized residual series.

Descriptive statistics, stationarity test, autocorrelation test, and arch effect test were carried out on the return change series r_t. Results show that the conditions for establishing the GARCH model are met. The fitted GARCH model results are in Table 6.

Next, the standardized residual sequence of a single GARCH sequence was used to establish the DCC-GARCH model. The estimation of the multivariate DCC-GARCH model is shown in Table 7. The results show that the binary DCC-GARCH model can be established respectively.

Table 6. Results of GARCH model

	TPPI	BANK	FUND
Model	ARMA(4,4)-GARCH(1,1)	ARMA(5,4)-GARCH(1,1)	ARMA(2,2)-GARCH(1,1)
AIC	-6.20944	-5.64546	-4.53838
SC	-6.134709	-5.570657	-4.486742
R^2	0.077054	0.146801	0.049039
Residual ARCH effect	none	none	none

Table 7. Coefficient estimation result of DCC-GARCH model

	TPPI-BANK	TPPI-FUND	BANK-FUND
α	0.032392	0.016405	0.003811
β	0.929566	0.932758	0.971611
$\alpha+\beta<1$	significant	significant	significant

Table 8. ΔCoVaR between two different IMMFs

Year	TPPI→FUND	FUND→TPPI	TPPI→BANK	BANK→TPPI	FUND→BANK	BANK→FUND
2015	-0.03551	-0.0131	0.000838	0.000811	-0.01376	-0.03196
2016	-0.02513	-0.01075	-0.01281	-0.01486	-0.00793	-0.01659
2017	-0.0108	-0.00849	-0.00933	-0.00882	-0.00538	-0.00788
2018	-0.01352	-0.00493	-0.0063	-0.00455	-0.0034	-0.00686
Average	-0.02124	-0.00932	-0.0069	-0.00685	-0.00762	-0.01582

NOTE: → indicates the direction of risk spillover.

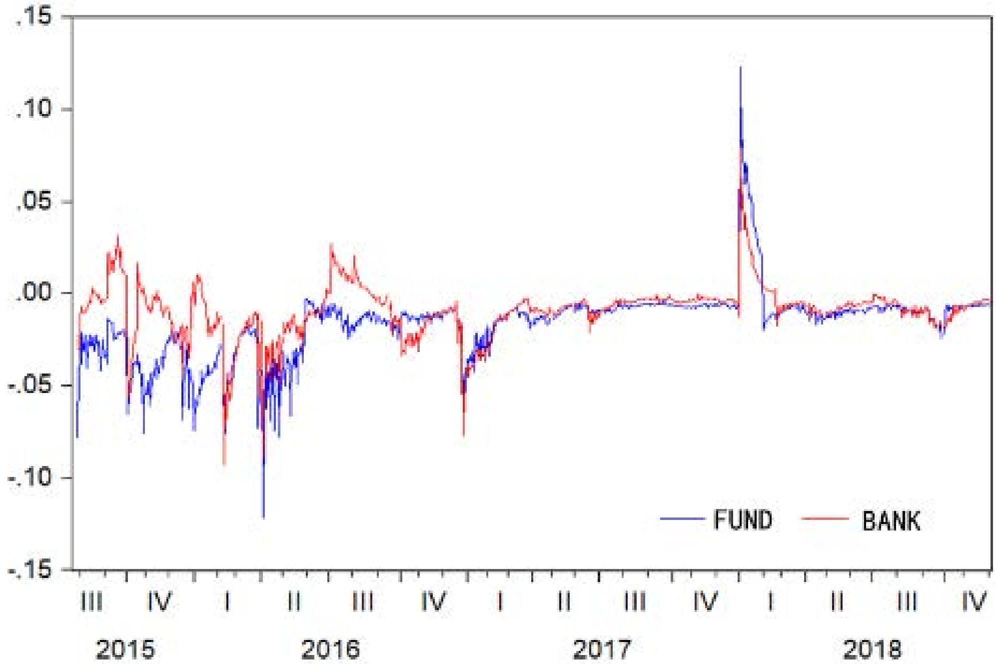
5.2 Risk Spillover Effect Analysis

According to the fitted DCC-GARCH model, the correlation coefficients between different series of IMMFs were calculated. The results of the liquidity risk spillover effect are shown in Table 8.

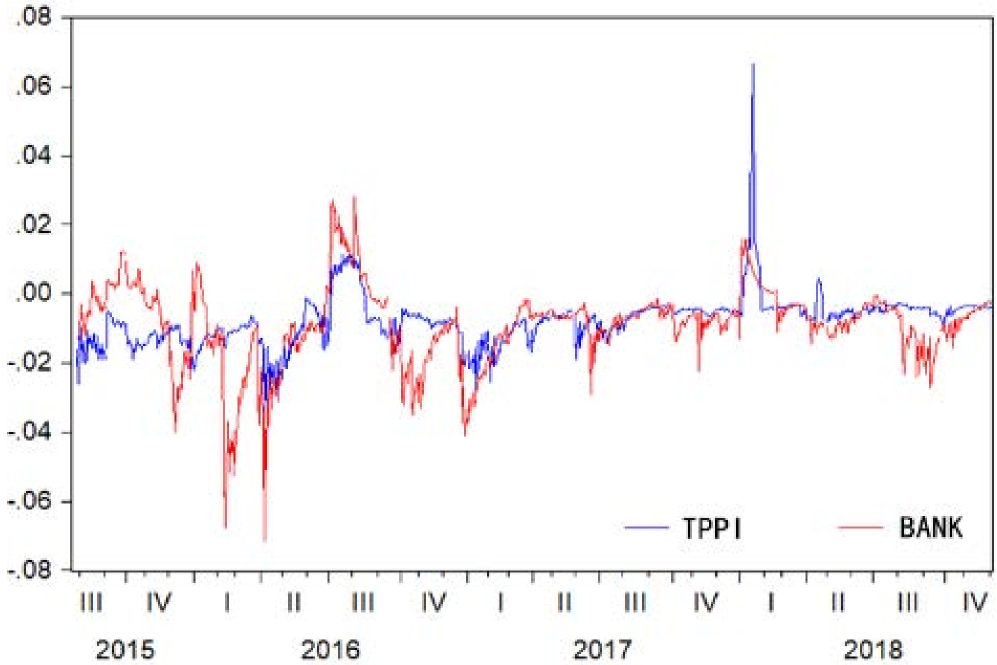
Table 8 shows that the liquidity risk spillover effect from IMMFs docked byTPPI to other IMMFs is slightly more substantial than that in the opposite direction, which indicates that IMMFs docked by BANK and FUNDare more vulnerable. The reasons might include: (a) IMMFs docked by TPPI have the payment function, which requires higher liquidity. (b) IMMFs docked by TPPI generally have a large scale. (c) IMMFs docked by BANK and FUND are mainly attached to Yu'E Bao, and they are highly dependent on the third-party payment system.

The risk spillover trend of IMMFs is shown in Figure 2.

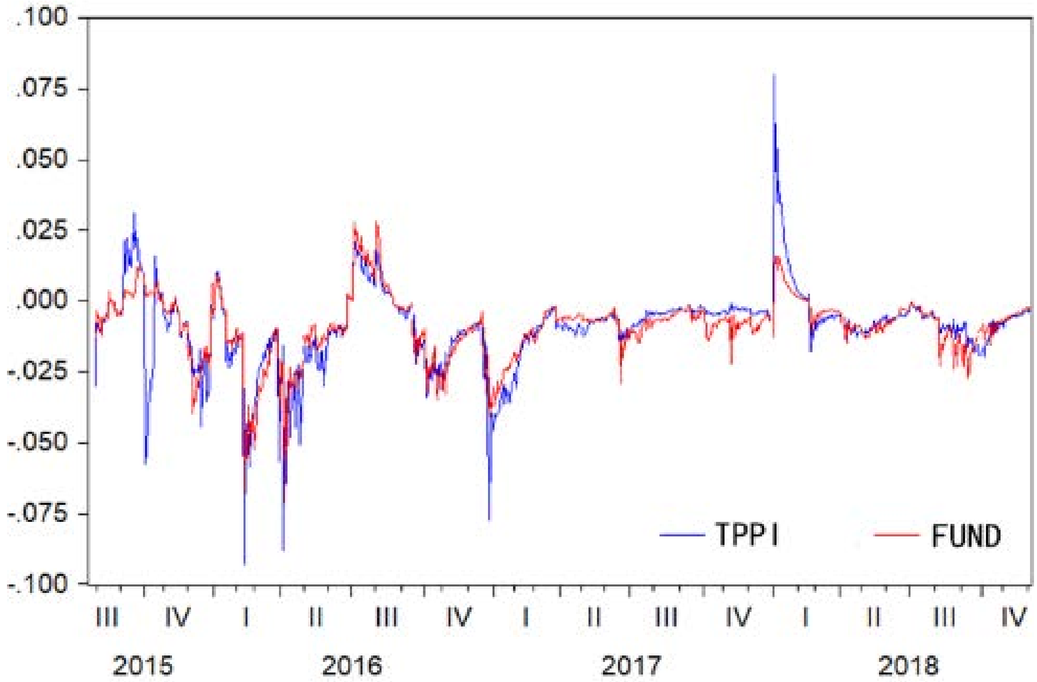
The spillover effect among different IMMFs shows a weakening trend. The effect reached the minimum in 2018 because of the strict regulation since 2017. Compared with figure (a), (b), (c) in Figure 2, the liquidity risk spillover among the three types of IMMFs show the same periodicity and has more substantial liquidity risk spillover than usual in the third and fourth quarters of 2015, the second and third quarters of 2016 and the fourth quarter of 2017. Most IMMFs invest in deposits, treasury bonds, resale securities, and inter-bank deposits. Events such as the central bank's interest rate cuts and RRR cuts will significantly increase the liquidity risk spillover. Therefore, the liquidity risk spillover effect between different IMMFs exhibits the same periodicity.



(a) Risk spillover from TPPI to BANK and FUND



(b) Risk spillover from FUND to TPPI and BANK



(c) Risk spillover from BANK to TPPI and FUND

Figure 2. Risk spillover trend of IMMFs

In summary, there is indeed a two-way liquidity risk spillover effect between different IMMFs, and the effect is asymmetric. We found that IMMFs docked by TPPI have a relatively more significant liquidity risk spillover effect on other IMMFs. Simultaneously, the spillover effect has continued to weaken over time and shows the same cyclical nature.

5.3 Liquidity Risk Contagion Path of IMMFs

Based on the above analysis, we verified that IMMFs are closely related, and there is a substantial risk of spillover between them. Therefore, to prevent the occurrence of systemic liquidity risks in the IMMFs market, exploring the contagion paths of liquidity risks between IMMFs is very important.

5.3.1 Calculation of Distance Matrix

MST algorithm is an essential part of a complex network [19]. The core idea is that the sum of the weights of the distance between each node is the most minor [20]. The network's robust connectivity is conducive to exploring the direction and path of risk contagion in the financial market. Therefore, our research used different IMMFs as nodes in the complex network and the distance length of the return rate change sequence as the weight connecting each node to explore the risk contagion path of IMMFs.

The first-order logarithmic difference method was used to process the return rates of different IMMFs to obtain the return rate change sequence. And then, the processed series were used to calculate the correlation coefficients of any two IMMFs to establish the correlation coefficient matrix. The correlation coefficient of IMMF i and j can be expressed as:

$$\rho_{ij} = \frac{E(R_i R_j) - E(R_i)E(R_j)}{\sqrt{[E(R_i^2) - (E(R_i))^2][E(R_j^2) - (E(R_j))^2]}} \quad \textbf{(20)}$$

Where $E(g)$ represents the mean value of the sequence of changes in the rate of return, and $E(R_i) = \frac{1}{N}\sum_{i=1}^{N} R_i$, $E(R_j) = \frac{1}{N}\sum_{j=1}^{N} R_j$, $E(R_i R_j) = \frac{1}{N^2}\sum_{i,j=1}^{N} R_i R_j$, $E(R_i^2) = \frac{1}{N}\sum_{i=1}^{N} R_i^2$, $E(R_j^2) = \frac{1}{N}\sum_{j=1}^{N} R_j^2$.

Convert the correlation coefficient matrix to Euclid distance matrix, and the results would be used as the weight between each node in the IMMFs network,

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \quad \textbf{(21)}$$

Where $d_{ij} \in [0,2]$, only when $i = j$, $d_{ij} = 0$, $d_{ij} = d_{ji}$, $d_{ij} < d_{ik} + d_{kj}$, $i \neq j \neq k$ and $i, j, k \in N$.

Then, the risk contagion path of the IMMFs network was constructed based on the Kruskal algorithm of MST.

We use R_t to calculate the correlation coefficient between two IMMFs and establish the correlation coefficient matrix. Next, calculate the distance weight between two MST nodes based on equations (20) and (21). The calculation results of the distance matrix are shown in Appendix B.

5.3.2 Analysis of Liquidity Risk Contagion Path

MST algorithm was used to get the minimum spanning tree of different IMMFs. When a node of the IMMFs network receives the impact from internal factors (term mismatch, centralized cashing) or external factors (macroeconomic conditions, policy changes, etc.) to cause liquidity risk, the shortest path becomes the fastest contagion path, where liquidity risk would spread to the whole IMMFs market, and then cause systemic risk.

Figure 3 shows the liquidity risk contagion diagram of IMMFs generated by MST algorithm.

According to Figure 3, IMMFs with an extensive fund scale can quickly spread liquidity risk to the entire market. Those IMMFs located on the backbone of the risk contagion path have larger fund scales, and the risk contagion path between them is shorter. It can be inferred that the IMMFs with larger fund scales have a more significant correlation and strong risk contagion ability.

The risk contagion network started from Tianhong Yu'E Bao (000198) and then spread to Pingan Rizengli (000379) and Penghua Tianli Bao (001666), and then connected to Huitianfu. Heju Bao (000600), Huaan Huicaitong (000709), and other IMMFs docked by BANK and FUND.

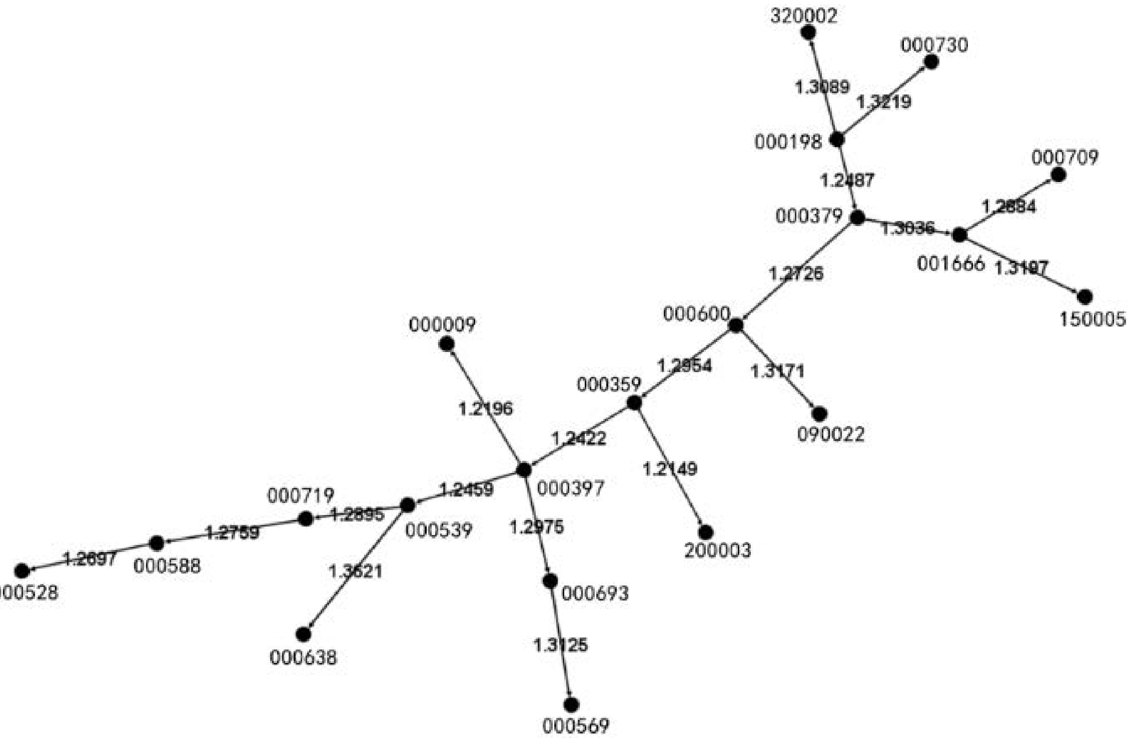


Figure 3. Risk contagion path diagram of IMMFs

The nodes in Figure 3 can be divided into two dense network blocks. One block contains Yifangda Yilicai (000359) and these IMMFs on its right, and the other one has Huitianfu Quan'e Bao (000397) and those IMMFs on its left. Node distribution shows that the Tianhong Yu'E Bao (000198) and Huitianfu Quan'e Bao (000397) are the center nodes of the two network blocks, which can radiate to other IMMFs. It indicates that IMMFs docked by TPPIhave more obvious systemic importance. The liquidity risk caused by fluctuations in their returns is more likely to infect other IMMFs. This, in turn, affects the stability of the entire IMMFs market.

To sum up, large-scale IMMFs or these docked by TPPI are located in the risk contagion network's critical position. Once they have liquidity risk, the risk would quickly spread to other IMMFs along with the MST network, accelerating systemic risk formation, which can easily cause the entire market to fall into a crisis.

6 Conclusions

This research introduces CUL to establish the risk measurement model La-VaR for IMMFs' liquidity risk evaluation. Empirical evidence reveals that the conventional VaR model underestimates the risk of IMMFs. In contrast, the La-VaR framework incorporating the liquidity risk can measure the risks faced by IMMFs more effectively. La-VaR results suggested that IMMFs docked by TPPI have relatively higher returns and meet the most severe liquidity risk. The yield of IMMFs docked by BANK ranks second, but their liquidity risk is relatively small. IMMFs from fund companies usually have a lower output and a higher liquidity risk. Besides, the case study of Yu'E Bao shows that liquidity risk influences the IMMFs remarkably, which indicates that it is of great importance to evaluate the liquidity-adjusted risk of IMMFs.

Also, the empirical analysis shows a robust two-way risk spillover effect between different types of IMMFs, but the effect is asymmetry. IMMFs docked by TPPI have the most substantial liquidity risk spillover effect. Moreover, the liquidity risk spillover effects between different types of IMMFs continue to weaken over time and be affected by the macroeconomic cycle.

Still, the research results cannot cover all the IMMFs and the internet finance market situations. In future research, the data samples should be expanded, and the liquidity risk measurement methods of IMMFs can be optimized.

Furthermore, our future work might make a more detailed comparison between the spillover effect using different CoVaR models.

Acknowledgments

This work was funded by the Natural Science Foundation of Shandong Province (No. ZR2018BG002), P.R. China, the Scientific Research Foundation of Shandong University of Science and Technology (No. 2017RCJJ066), the Shandong Statistical Scientific Research Fund (No. KT022), and the Postgraduate Research Fund of Shandong University of Science and Technology (No. 01040075165). Also, we would like to thank all the interviewees who participated in this study and shared their thoughts with us.

References

[1] H. Z. Ma, L. Lin, H. Sun, Y. Qu, Research on the Dependence Structure and Risk Spillover of Internet Money Funds Based on C-Vine Copula and Time-Varying t-Copula, *Complexity*, Vol. 2021, Article No. 3941648, August, 2021.

[2] R. D. Chen, H. W. Chen, C. L. Jin, B. Wei, L. A. Yu, Linkages and Spillovers between Internet Finance and Traditional Finance: Evidence from China, *Emerging Markets Finance and Trad*e, Vol. 56, No. 6, pp. 1196-1210, May, 2020.

[3] E. Bengtsson, Shadow Banking and Financial Stability: European Money Market Funds in the Global Financial Crisis, *Journal of International Money and Finance*, Vol. 32, pp. 579-594, February, 2013.

[4] H. H. Gao, S. Y. Mao, W. Q. Huang, X. X. Yang, Applying Probabilistic Model Checking to Financial Production Risk Evaluation and Control: A Case Study of Alibaba's Yu'e Bao, *IEEE Transactions on Computational Social Systems*, Vol. 5, No. 3, pp. 785-795, September, 2018.

[5] X. X. Yang, S. Y. Mao, H. H. Gao, Y. Duan, Q. Zou, Novel Financial Capital Flow Forecast Framework Using Time Series Theory and Deep Learning: A Case Study Analysis of Yu'e Bao Transaction Data, *IEEE Access*, Vol. 7, pp. 70662-70672, May, 2019.

[6] J. Q. Zhang, L. He, Y. B. An, Measuring Banks' Liquidity Risk: An Option-Pricing Approach, *Journal of Banking & Finance*, Vol. 111, Article No. 105703, February, 2020.

[7] A. Bangia, F. X. Diebold, T. Schuermann, J. Stroughair, *Modeling Liquidity Risk, with Implications for Traditional Market Risk Measurement and Management*, in: S. Figlewski, R. M. Levich (Eds), Risk Management: The State of the Art, Springer, 2001, pp. 3-13.

[8] Y. Jin, Optimal Execution Strategy and Liquidity Adjusted Value-at-risk, *Quantitative Finance*, Vol. 17, No. 8, pp. 1147-1157, August, 2017.

[9] K. Cortez, M. D. P. Rodriguez-Garcia, S. Mongrut, Exchange Market Liquidity Prediction with the K-nearest Neighbor Approach: Crypto vs. Fiat Currencies, *Mathematics*, Vol. 9, No. 1, Article No. 56, January, 2021.

[10] R. J. Xu, C. M. Mi, R. Mierzwiak, R. Y. Meng, Complex Network Construction of Internet Finance Risk, *Physica A-Statistical Mechanics and Its Application*s, Vol. 540, Article No. 122930, February, 2020.

[11] J. C. Dong, L. J. Yin, X. T. Liu, M. T. Hu, X. T. Li, L. Liu, Impact of Internet Finance on the Performance of Commercial Banks in China, *International Review of Financial Analysis*, Vol. 72, Article No. 101579, November, 2020.

[12] C. G. Zhao, M. Li, J. Wang, S. J. Ma, The Mechanism of Credit Risk Contagion among Internet P2P Lending Platforms Based on a SEIR Model with Time-Lag, *Research in International Business and Finance*, Vol. 57, Article No. 101407, October, 2021.

[13] X. Y. Fan, Y. D. Wang, D. P. Wang, Network Connectedness and China's Systemic Financial Risk Contagion--An Analysis Based on Big Data, *Pacific-basin Finance Journal*, Vol. 68, Article No. 101322, September, 2021.

[14] M. Bleaney, Z. Li, The Performance of Bid-ask Spread Estimators under Less than Ideal Conditions, *Studies in Economics and Finance*, Vol. 32, No. 1, pp. 98-127, March, 2015.

[15] H. Le, A. Gregoriou, How Do You Capture Liquidity? A Review of the Literature on Low-frequency Stock Liquidity, *Journal of Economic Surveys*, Vol. 34, No. 5, pp. 1170-1186, December, 2020.

[16] T. Adrian, M. K. Brunnermeier, CoVaR, *American Economic Review*, Vol. 106, No. 7, pp. 1705-1741, July, 2016.

[17] M. A. M. Al Janabi, R. Ferrer, S. J. H. Shahzad, Liquidity-adjusted Value-at-risk Optimization of a Multi-asset Portfolio Using a Vine Copula Approach, *Physica A-Statistical Mechanics and Its Applications*, Vol. 536, Article No. 122579, December, 2019.

[18] A. Czelleng, Market Liquidity and Funding Liquidity: Empirical Analysis of Liquidity Flows Using VAR Framework, *Acta Oeconomica*, Vol. 70, No. 4, pp. 513-530, December, 2020.

[19] D. Cheng, Q. Zhu, J. Huang, Q. W. Wu, L. J. Yang, Clustering with Local Density Peaks-based Minimum Spanning Tree, *IEEE Transactions on Knowledge and Data Engineering*, Vol. 33, No. 2, pp. 374-387, February, 2021.

[20] T. Millington, M. Niranjan, Construction of Minimum Spanning Trees from Financial Returns Using Rank Correlation, *Physica A-Statistical Mechanics and Its Applications*, Vol. 566, Article No. 125605, March, 2021.

Biographies

Huizi Ma received the B.S. and Ph.D. degrees from Harbin Engineering University in 2009 and 2014, respectively. She is currently a Lecturer in the College of Mathematics and System Science, Shandong University of Science and Technology. Her research interests mainly include fintech and financial statistics.

Yuting Wang received her Master degree in Finance in Shandong University of Science and Technology in 2019. Her main research interests include Internet finance and risk evaluation.

Lin Lin is currently pursuing the M.S. degree in Statistics in Shandong University of Science and Technology, and her current research interests include neural networks and their application in statistics.

Xiangrong Wang received the Ph.D. degree in applied mathematics from Shandong University in 1998. He is currently a Professor in Shandong University of Science and Technology. His research interests include stochastic control theory, forward and backward stochastic differential equations, and mathematical finance.

Appendix A

Information of sample IMMFs

IMMFs		Internet financial product	Platform	IMMF	Fund Code
(a)	IMMFs docked by online third party payment Institutions	Yu'E Bao	AntFinancial	TianhongYu'E Bao	000198
		Lingqian Bao	Suning Finance	PenghuaTianli Bao	001666
		TecentLicaitong	TencentTenpay	PinganRizengli	000379
				PenghuaZengzhi Bao	000569
				HuitianfuQuan'e Bao	000397
				NanfangXianjintong E	000719
		Yu'E Ying	Baidu Finance	YifangdaTiantian A	000009
		Fuqian Bao	China Unicom	FuguoFuqianbao	000638
(b)	IMMFs docked by banks	Kuaixian Bao	Shanghai Bank	YifangdaYilicai	000359
				HuitianfuHeju Bao	000600
				BoshiXianjin Bao A	000730
		Suying	China Construction Bank	JianxinXianjintianli A	000693
		Xinjin Bao	Industrial and Commercial Bank of China	GongyinXinjinhuobi A	000528
		Xingye Bao	China Industrial Bank	DachengXianjinzengli	090022
		Zhaozhao Ying	China Merchants Bank	ZhaoshangZhaoqian Bao A	000588
(c)	IMMFs docked by the fund companies	Huoqi Bao	Bank of China Investment Management	ZhongyinHuoqi Bao	000539
		Xianjin Bao	Great Wall Fund	Changcheng Huobi A	200003
		Weiqian Bao	HuaAn Funds	HuaanHuicaitong	000709
		Beili Bao	Galaxy AMC	YinheYinfuhuobi A	150005
		Lion XIanjin Bao	Lion Fund	Nuoan Huobi A	320002

Appendix B

Distance matrix between IMMFs

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.0000																			
2	1.3418	0.0000																		
3	1.2487	1.3036	0.0000																	
4	1.3996	1.4300	1.4461	0.0000																
5	1.4140	1.4023	1.4026	1.3604	0.0000															
6	1.3529	1.4190	1.3184	1.3461	1.4216	0.0000														
7	1.4381	1.4153	1.4626	1.4109	1.2196	1.3877	0.0000													
8	1.3850	1.4256	1.3949	1.4744	1.4102	1.4512	1.3761	0.0000												
9	1.4073	1.3466	1.3204	1.3354	1.2422	1.4717	1.3738	1.4412	0.0000											
10	1.3616	1.3921	1.2726	1.4838	1.3824	1.5101	1.3995	1.4619	1.2954	0.0000										
11	1.3219	1.3691	1.3848	1.4478	1.4539	1.4479	1.4412	1.4316	1.4220	1.4071	0.0000									
12	1.3340	1.3956	1.3715	1.3125	1.2975	1.4386	1.3144	1.4293	1.3243	1.3285	1.4521	0.0000								
13	1.4434	1.4230	1.4950	1.3471	1.3909	1.4461	1.3598	1.3807	1.3362	1.4088	1.4650	1.3249	0.0000							
14	1.3515	1.3496	1.3893	1.4884	1.3900	1.4845	1.4069	1.3892	1.3673	1.3171	1.3835	1.3756	1.4660	0.0000						
15	1.2965	1.4445	1.3684	1.3606	1.4329	1.2759	1.3820	1.4387	1.4037	1.3976	1.3357	1.3499	1.2697	1.3657	0.0000					
16	1.4120	1.4106	1.4305	1.4279	1.2459	1.2895	1.2761	1.3621	1.3979	1.4043	1.3831	1.3600	1.3816	1.3779	1.3789	0.0000				
17	1.4425	1.3920	1.3086	1.3657	1.3601	1.4412	1.3590	1.4542	1.2149	1.3306	1.3892	1.3948	1.3555	1.4348	1.3317	1.4997	0.0000			
18	1.4666	1.2884	1.4043	1.3893	1.3840	1.4748	1.3776	1.3990	1.3702	1.4036	1.3353	1.3437	1.3175	1.3694	1.4494	1.3843	1.3561	0.0000		
19	1.3901	1.3197	1.4172	1.3880	1.4244	1.3801	1.3929	1.4504	1.3575	1.3953	1.4037	1.3922	1.3276	1.4328	1.3684	1.3304	1.3570	1.3280	0.0000	
20	1.3089	1.3651	1.3955	1.3844	1.3815	1.4161	1.3649	1.4218	1.3986	1.4227	1.3969	1.3614	1.3914	1.3748	1.3890	1.4133	1.3808	1.4116	1.4112	0.0000